Use of Morphological Signal Processing and Computational Intelligence for System Prognostics

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Presentation Summary

- Introduction-PHM
- Morphological Signal Processing
- Time Series Prediction
  - Recursive Neural Network (RNN)
  - Adaptive Neuro-Fuzzy Inference System (ANFIS)
  - Support Vector Regression (SVR)
- Comparison of Prediction Performance
- Machine Condition Prognosis
  - Monitoring Index
- Results and Discussions
  - Training Datasets
  - Test Case
- Conclusions
- Future Work

Introduction 1/4

- Prognostics & Health Management (PHM)
  - Gaining importance in mission critical systems
    - Aerospace
    - Military
    - Commercial applications
  - Important for effective utilization and maintenance in CBM
- PHM combines
  - Prognostic capability for estimation of remaining useful life (RUL)
  - Health management through informed decisions on operational, maintenance and logistics actions.

Introduction 2/4

- Different approaches of prognostics include
  - dynamical systems approach,
  - data-driven prognostics,
  - the fusion of failure dynamics with diagnostic data

Introduction 3/4

- Machine State prediction using a ‘Monitoring Index’ based on
  - Time domain features
  - Frequency spectrum
  - Time-frequency domain features (wavelet transform)
  - Signal energy
    - Energy Index (EI)
    - Entropy

Introduction 4/4

- Different data-driven techniques include
  - Artificial neural networks (ANN)
  - Support vector machines (SVM)
  - Fuzzy Logic
  - Neuro-Fuzzy (NF) systems

The present work

- Compares time-series prediction capability of
  - Recursive Neural Network (RNN)
  - Adaptive Neuro-Fuzzy Inference System (ANFIS)
  - Support Vector Regression (SVR)

  Using
    - training datasets
      - sunspot activity
      - Duffing oscillator response
    - Test dataset of a helicopter drivetrain gearbox
    - Entropy based feature through morphological signal processing (MSP)

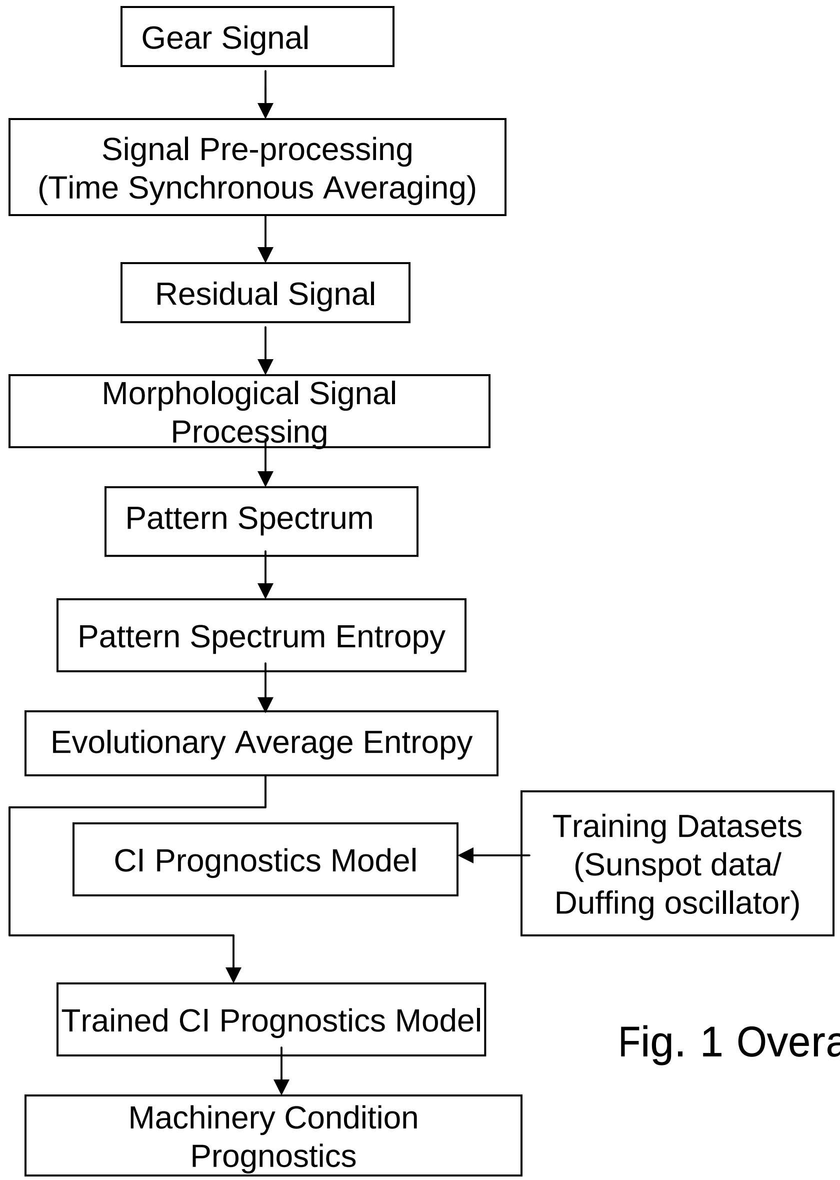


Fig. 1 Overall schematic of machine prognostics

Morphological Signal Processing

- It is based on set-theoretical method of nonlinear analysis called mathematical morphology (MM)
- It involves extraction of signal shape and size features through morphological operations, namely, erosion, dilation, opening and closing using a simpler object termed as structuring element (SE) [22] .
- Erosion:
- Dilation:
- Opening:
- Closing:

$$(f \ominus g)(i) = \min\,(f(i+j) - g(j)],\ j \in 0,1,2,..\,J-1, \quad (1)$$

$$(f \oplus g)(i) = \max\,(f(i-j) + g(j)],\ j \in 0,1,2,..\,J-1 \quad (2)$$

$$(f \circ g)(i) = ((f \ominus g) \oplus g)(i) \quad (3)$$

$$(f \bullet g)(i) = ((f \oplus g) \ominus g)(i) \quad (4)$$

Where $\ominus$, $\oplus$, $\circ$ and $\bullet$ denote the morphological operators for erosion, dilation, opening and closing respectively.

Multiscale Morphology Analysis

- Traditional MM used single-scale analysis with a SE of fixed scale (size) selected a priori based on the nature of the signal to be analyzed.
- Very often it is not possible to have the prior knowledge for selecting the scale of SE in single-scale applications.
- To overcome this shortcoming, multiscale morphological filters (MMF) along with pattern spectrum (PS) were proposed.
- SEs of scales (n=0,1,2,..N-1) are used for morphological analysis.
- For a discrete-valued function *g(j)*, $j \in J$, used as the basic SE, the function pattern can be defined as follows:

$$\begin{cases} ng = g \oplus g \oplus g \ldots \oplus g \ \ (n\,times), \\ 0g = \{0\}. \end{cases} \tag{5}$$

Pattern Spectrum

- For a nonnegative sampled signal, $f(i),\ i \in I$ and a SE g, the pattern spectrum (PS) are defined as follows [24]:

$$PS(f,g,+n) = S[f \circ ng - f \circ (n+1)g], \quad 0 \le n \le N \qquad (6)$$

$$PS(f,g,-n) = S[f \bullet ng - f \bullet (n-1)g], \quad 1 \le n \le K \qquad (7)$$

$$PS(f,g,n) = S[f \circ ng] - S[f \circ (n+1)g] \ge 0 \quad \forall n \ge 0$$

$$S(f) = \sum_i f(i)$$

- The pattern spectrum contains useful qualitative information about the signal (f) relative to the SE (g). The lower part of PS manifests the roughness of f relative to g. The degree of shape content of g in f is given as $PS(f,g,n)/S(f)$

Pattern Spectrum Entropy

- The quantitative measure of shape-size complexity of a signal relative to a SE pattern can be obtained based on its PS in form of average roughness using information theory as follows:

$$H(f/g) = -\sum_{n=0}^{N} q(n) \log q(n)$$

$$q(n) = PS(f,g,n) / S(f)$$

$$H_r(f/g) = H(f,g,n) / \log(N+1)$$

Evolutionary Pattern Spectrum Entropy

- A way of representing the variation over the period is to use its evolutionary *a*verage. In the present work, a similar index namely evolutionary average pattern spectrum entropy (aH_r) at time (cycle) index $p(>0)$, is introduced as follows:

$$aH_r(p) = \frac{1}{p} \sum_{l=1}^{p} H_r(l)$$

Time Series Prediction

- The value at *r*-time step ahead , x_{t+r}

in terms of values previous steps:

$$x_{t-mr}, x_{t-(m-1)r}, \ldots \; x_{t-r}, x_t$$

$$x_{t+r} = \phi(x_{t-mr}, x_{t-(m-1)r}, x_{t-(m-2)r}, \ldots x_{t-3r}, x_{t-2r}, x_{t-r}, x_t), \quad m,r > 0$$

- Techniques used :
  - RNN
  - ANFIS
  - SVR

Machine Condition Prognosis

- Monitoring Index
  - Characterizing the fault progression
- Type of faults considered
  - Gear tooth failure
    - for a helicopter drivetrain gearbox (US Navy)

Results and Discussions

- Training dataset
  - Normalized dataset of sunspot activity (1700-2005)
  - Duffing oscillator
- Test dataset-gear tooth failure
  - Signal preprocessing
  - Pattern spectrum extraction
  - Evolutionary average entropy
    - (monitoring index)

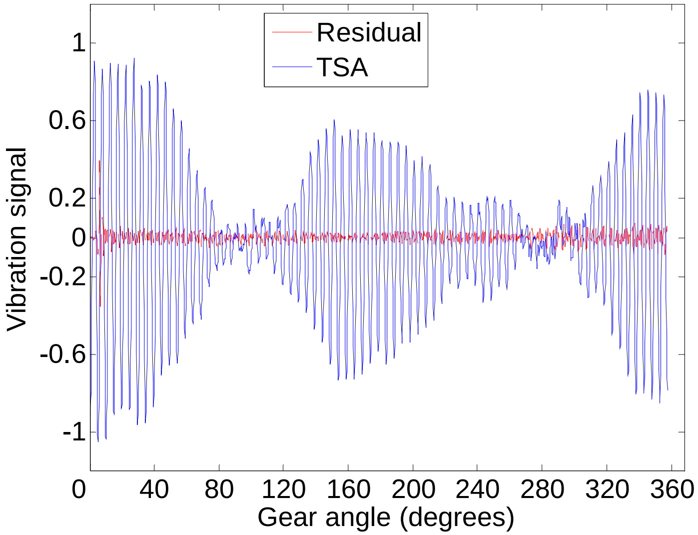


Fig. 2. Preprocessed vibration signal of a helicopter drivetrain gearbox [18]

Extraction of Monitoring Index for Prognosis

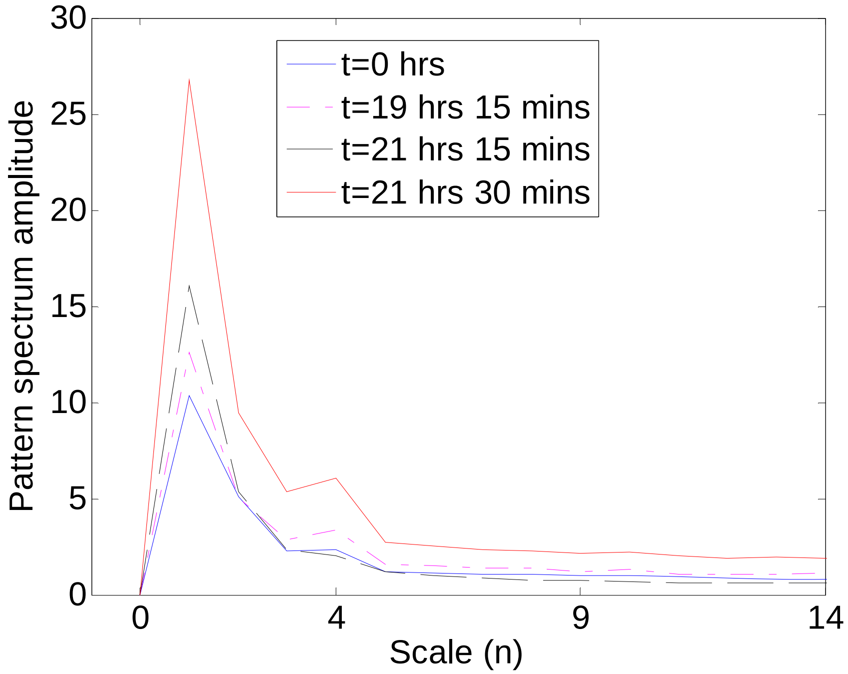


Fig.3. Pattern spectrum of residual signals

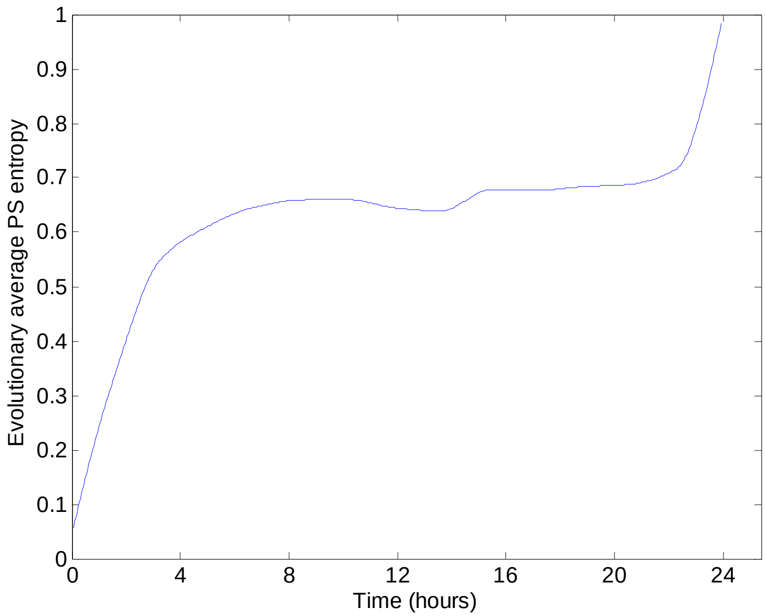
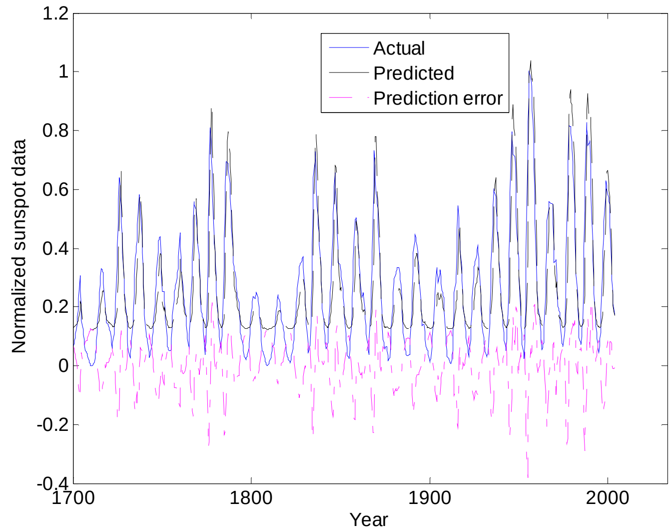
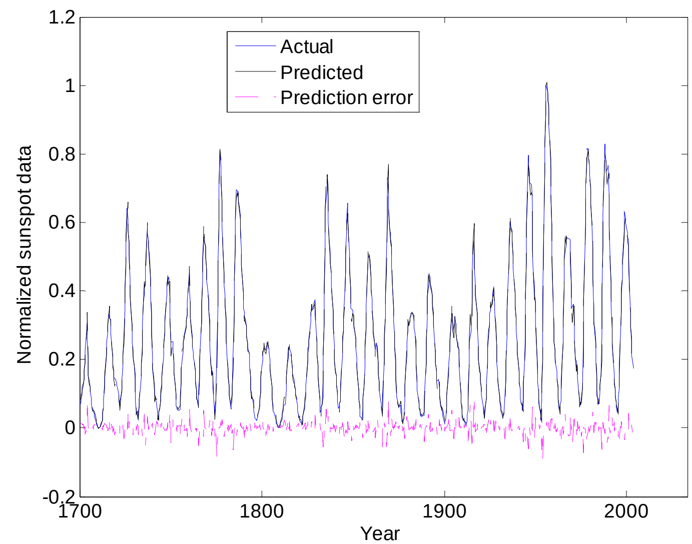


Fig.4. Evolutionary average pattern spectrum entropy

Training Results (Sunspot data)



(a)



(b)

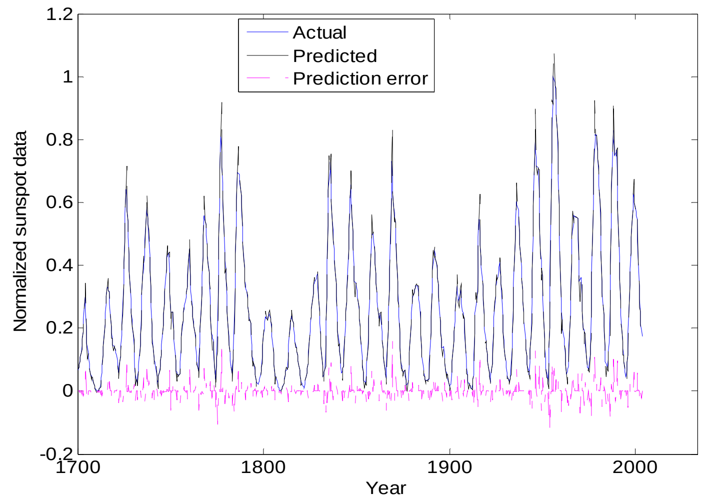
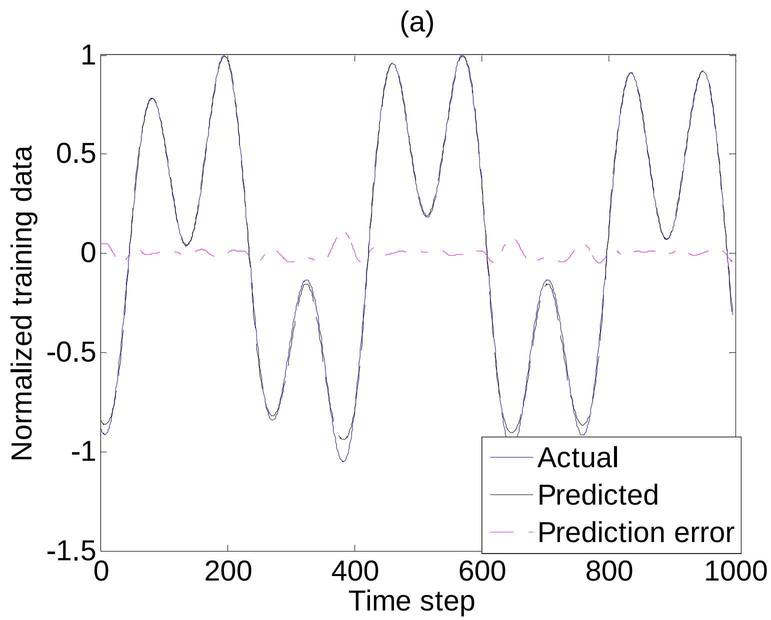


Fig. 5. Training results for sunspot activity data [26], (a) RNN, (b) ANFIS, (c) SVR.

(c)

Training Results (Duffing oscillator)



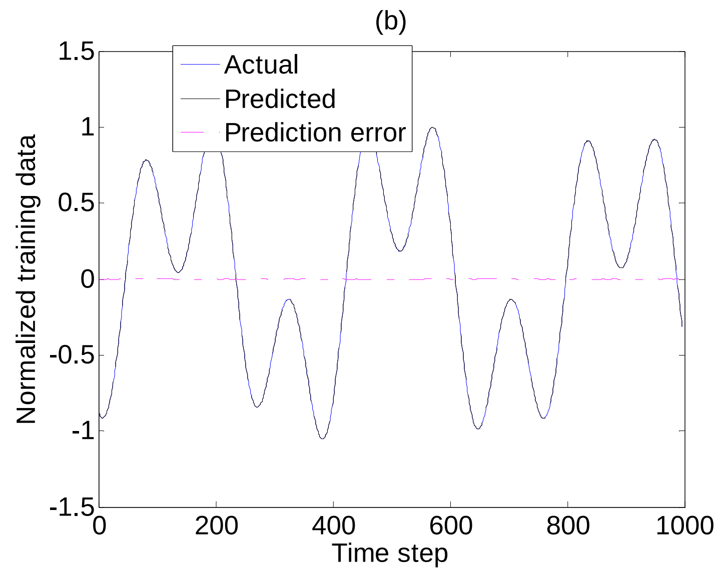
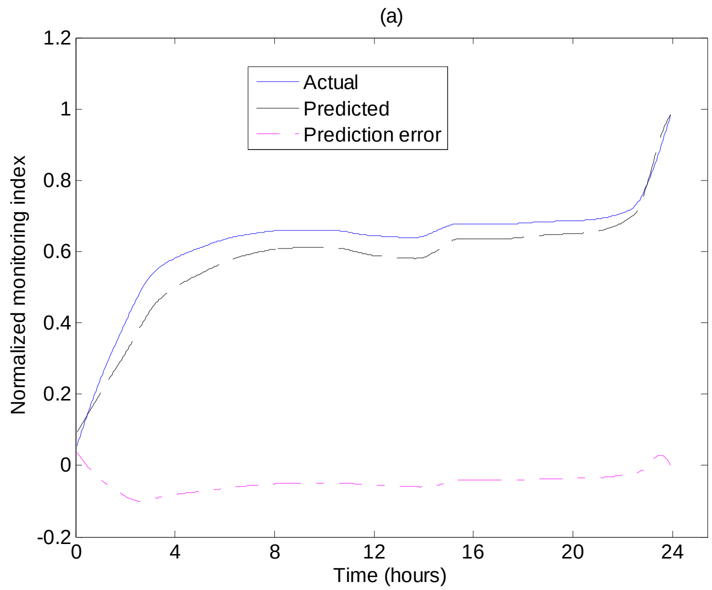
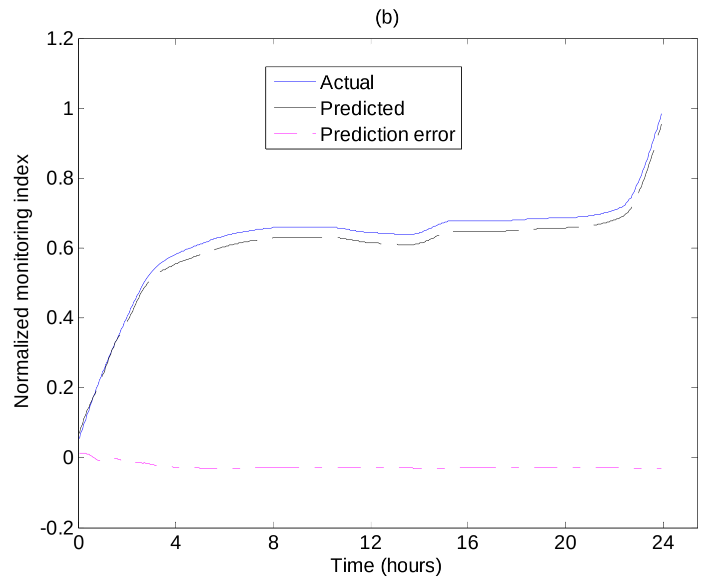


Fig. 6. Training results of Duffing oscillator response (a) RNN, (b) ANFIS and SVR.

Prediction Comparison





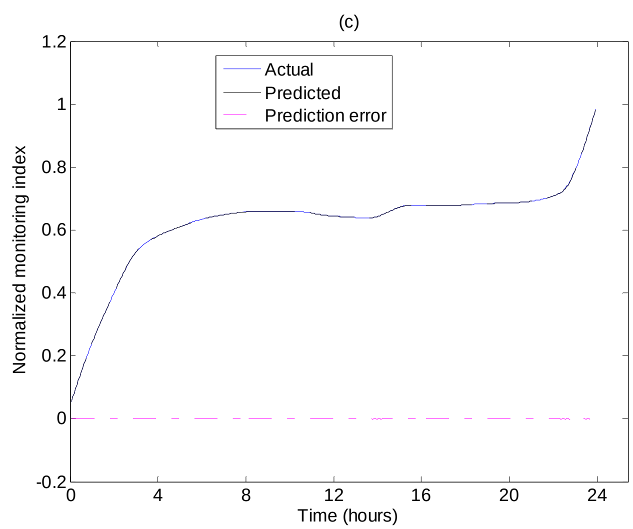


Fig. 7. Test results for gear failure prognostics using training dataset of sunspot activity (a) RNN, (b) ANFIS, (c) SVR

Prediction Comparison

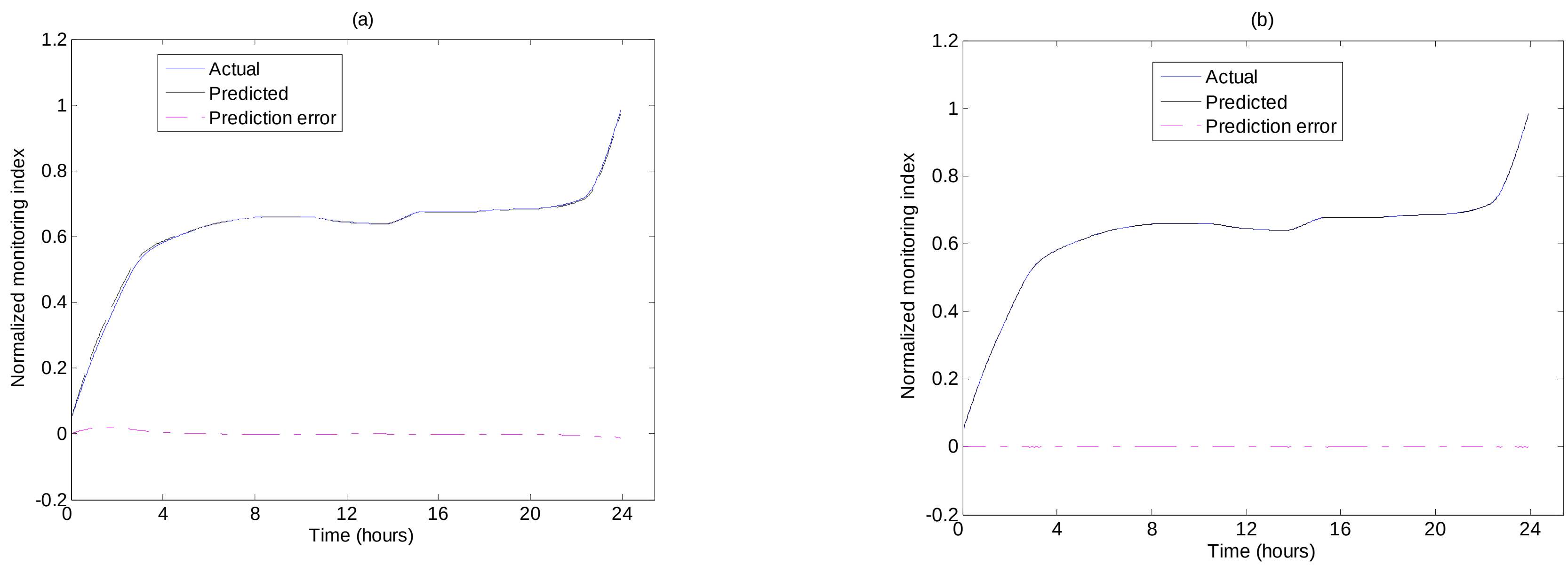


Fig. 8. Test results for gear failure prognostics using training dataset of Duffing oscillator (a) RNN, (b) ANFIS and SVR.

Comparison of Prediction Performance

Method	Training with sunspot data			Training with Duffing oscillator		
	Training time (sec)	Training RMSE	Test RMSE	Training time (sec)	Training RMSE	Test RMSE
RNN	99.2	0.099	0.040	113.0	0.029	0.007
ANFIS	25.5	0.017	0.028	0.4	0.834×10^{-4}	0.413×10^{-3}
SVR	1430.4	0.023	0.341×10^{-3}	2014.2	0.702×10^{-3}	0.425×10^{-3}

TABLE I Prediction Results for Gear Pattern Spectrum Evolutionary Average Entropy Index

Conclusions

- The work proposed a novel entropy based feature as a 'monitoring index' using morphological signal processing.
- It presented comparison of 3 predictors: RNN, ANFIS and SVR.
- It illustrated the procedure through a helicopter drivetrain gearbox dataset.
- Training based on Duffing oscillator response gave better results than using sunspot data for all 3 predictors.
- Comparable training performance of ANFIS and SVR
- Test performance of SVR was found to be better than ANFIS and RNN using sunspot data.
- The training time of SVR was much higher than ANFIS.
- When trained with Duffing oscillator response, test results of ANFIS and SVR were similar.
- Results show the effectiveness of the predictors in estimating the variations of the monitoring index.

Future Work

- Extension to multi time step ahead prediction.
- The potential application of these techniques for development of on-line prognostic systems for machine condition need further work.
- Validation of the techniques using a wider data base
- Integrated model development combining data-driven results with physics-based approach for better understanding of the process.

Acknowlegments

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